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Online oscillation detection in the presence of signal intermittency

Lei Xie [a,*], Xun Lang [a,*], Alexander Horch [b], Yuxi Yang [a]

[a] State Key Laboratory of Industrial Control Technology, Zhejiang University, 310027 Hangzhou, China
[b] HIMA Paul Hildebrandt GmbH, 68782 Bruehl bei Mannheim, Germany

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ABSTRACT

A novel online detector for multiple oscillations in process industry is proposed. This article is motivated by the fact that it is still an open problem to design a real-time monitor which is suitable for detecting multiple oscillations with signal intermittency and non-linear/non-stationary properties. The proposed approach of Intrinsic Time-scale Decomposition (ITD) with Robust Zero crossing intervals Clustering (ITD-RZC) (i) provides an experimental statistic to remove noisy zero-crossings intervals (ZCIs), (ii) develops a novel adaptive robust K-means ZCI clustering which enables the reconstructed Proper Rotation Component (PRC) to encapsulate the sporadic oscillation and (iii) proposes an effective online-cluster-updating mechanism for real-time intermittent oscillations detection. ITD-RZC approach is computationally efficient and capable of preserving nonlinear features of the process variables which facilitates subsequent oscillation diagnosis. Simulation examples and industrial cases study are provided to demonstrate the effectiveness of the proposed online oscillation detector.

1. Introduction

Oscillation is a common type of abnormal phenomenon encountered in process industries. The presence of oscillatory behavior in a control loop may cause inferior products, larger rejection rates, increased consumption of energy, and even compromise process stability (Thornhill, Huang, & Zhang, 2003). Therefore, the detection of oscillations in univariate time series is of significant importance. The last two decades have witnessed a rapid development of the research in the fields of control system performance assessment as well as oscillation detection (Jelali & Huang, 2009).

Existing oscillation detection techniques can be roughly categorized as off-line and on-line ones. Most of the existing methods are off-line procedures. Hägglund (1995) first proposed an idea based on the integral of absolute control error (IAE) between its successive zero-crossings. Thornhill et al. (2003) utilized the zero crossings of auto-covariance (ACF) function for oscillation detection and period estimation. Jiang, Choudhury, and Shah (2007) proposed the spectral envelop method for both oscillation detection and root cause diagnosis. Recent methods have realized the oscillation detection for non-stationary and non-linear time series, including wavelet transform (WT) (Matsuo, Sasaoka, & Yamashita, 2003), modified empirical mode decomposition (EMD) (Srinivasan & Rengaswamy, 2012; Srinivasan, Rengaswamy, & Miller, 2007) and discrete cosine transform (DCT) (Li, Wang, Huang, & Lu, 2010).

On the other hand, methods for online oscillation detection are rarely available in the literature. Although most of the off-line techniques can be implemented on-line with a moving supervision window, difficulty exists in selecting a proper window size (Guo, Xie, Ye, & Horch, 2014). It is due to the simple fact that detecting a slow but regular oscillation component usually requires more samples to monitor the process, while high-frequency oscillations with shorter periods can be discovered earlier than the slow ones. Another type of online oscillation detection techniques relates to the inspection of the process data sample-by-sample. Hägglund (1995, 2005) utilized the IAE method to design a window-free real time oscillation detector. Salsbury and Singhal (2005) proposed an auto-regressive and moving-average (ARMA) modeling approach for online oscillation detection. These approaches, however, cannot deal with the multiple oscillations in single time series.

To overcome the difficulty of detecting oscillation within signals exhibiting multiple oscillation frequencies, WT (Matsuo et al., 2003) and DCT (Li et al., 2010) are commonly adopted as pre-defined dictionary matrices to extract the oscillatory components in original signal. Wang, Huang, and Lu (2013) proposed a modified DCT to approximate the real time oscillatory behavior with an adaptive supervision window. However, it still faces a difficult choice between the promptness and reliability of oscillation detection. EMD based method is proposed (Srinivasan & Rengaswamy, 2012) for online oscillation detection which can preserve the nonlinear features of the original signal. Note that a successful EMD application depends on careful treatments of end

* Corresponding authors.
E-mail addresses: leix@iipc.zju.edu.cn (L. Xie), 21432058@zju.edu.cn (X. Lang).

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effect (Cheng, Yu, & Yang, 2007), model mixing (Huang et al., 2003), intrinsic mode functions (IMF) criterion (Cheng, Yu, & Yang, 2006, 2012), etc. Recently, the authors have presented an online detector for time-varying/multiple oscillation characterization using improved ITD (iITD) method (Guo et al., 2014). The original ITD is improved by modifying its iteration termination condition and an online back-redecomposition procedure is proposed.

ITD decomposes a signal into a series of Proper Rotation Components (PRC) (Frei & Osorio, 2007) with different frequencies. The first PRC extracted by ITD contains the highest frequency components whilst the subsequent PRC has lower frequency. Despite its high computational efficiency and ability of separating multi-oscillation signals, the decomposition results of original ITD/iITD are apt to be distorted by signal intermittency, of which the intermittent oscillation is a typical case. For example, if an intermittent oscillatory component is injected into a signal, ITD/iITD will automatically rearrange PRCs to ensure that their frequency is decreasing successively. Consequently, a single PRC may comprise mixture of persistent and intermittent oscillation with different disturbances, or a single persistent oscillation may reside into different PRCs. Such phenomenon is termed as *level-jumping* in this study. Due to this phenomenon, ITD/iITD may fail to identify underlying oscillation when the process data possess the following features: (i) Noisy components in the process data hold some intermittent characteristics or their frequency varies in a discontinuous form and (ii) one or more intermittent oscillatory components occur in control loops due to operation condition change.

To resolve the above problem, this paper proposes a novel Intrinsic Time-scale Decomposition (ITD) with Robust Zero crossing intervals Clustering (ITD-RZC) approach. The main contributions and benefits of the proposed approach include (i) an experimental statistic to remove noisy zero-crossings intervals (ZCI), (ii) a novel adaptive robust K-means clustering which enables the reconstructed PRCs to encapsulate the sporadic oscillation for *level-jumping* phenomenon elimination and (iii) an effective mechanism of updating ZCI clustering model for the purpose of online intermittent oscillations detection.

The remainder of this paper is organized as follows. The basic ITD and K-means clustering algorithms are introduced in Section 2. Section 3 explains the *level-jumping* phenomenon of ITD/iITD with a numerical study. Section 4 elaborates the statistical distribution of ZCI by experimental study for PRCs of Gaussian white noise and develops a statistic for removing noisy intervals. Robust ZCI clustering and PRC reconstruction are also detailed in Section 4 with an illustrative example. Section 5 provides the implementation of online oscillation detector with a simulation application. Two industrial case studies are discussed in Section 6, which is followed by a summary in Section 7.

2. Preliminaries

2.1. Intrinsic time-scale decomposition

ITD decomposes a signal into (i) a sum of proper rotation components, for which instantaneous frequency and amplitude are well defined, and (ii) a monotonic trend as a residual signal (Frei & Osorio, 2007). Given an original signal $x(n)$, define the baseline-extracting operator $\mathcal{L}$ and proper-rotation-extracting operator $\mathcal{H}$, which extracts $x(n)$ into a baseline signal L_n in a manner that causes the residual H_n to be a proper rotation. More specifically, $x(n)$ can be decomposed as

$$x(n) = \mathcal{L}x(n) + (1 - \mathcal{L})x(n) \triangleq \mathcal{L}x(n) + \mathcal{H}x(n) = L_n + H_n \quad (1)$$

Let $\{\tau_k, k = 1, 2, \ldots\}$ denote the local extrema instants of $x(n)$, and $\tau_0 = 0$. Suppose that L_n has been defined on τ_k and $x(n)$ is available for $[\tau_k, \tau_{k+2}]$. For simplicity, let X_k and L_k denote $x(\tau_k)$ and $L_n(\tau_k)$, respectively. A piece-wise linear baseline and proper rotation of $x(n)$ on interval $[\tau_k, \tau_{k+1}]$ can be decomposed as follows:

$$\mathcal{L}x(n) = L_n = L_k + \left(\frac{L_{k+1} - L_k}{X_{k+1} - X_k}\right)\left(x(n) - X_k\right), \; n \in (\tau_k, \tau_{k+1}] \quad (2)$$

$$\mathcal{H}x(n) = H_n = (1 - \mathcal{L})x(n) = x(n) - L_n, \; n \in (\tau_k, \tau_{k+1}] \quad (3)$$

$$L_{k+1} = \alpha\left[X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k}\right)\left(X_{k+2} - X_k\right)\right] + \left(1 - \alpha\right)X_{k+1} \quad (4)$$

where $0 < \alpha < 1$ is typically selected around 0.5. Since $x(n)$ is monotonic on interval $(\tau_k, \tau_{k+1}]$, with L_n and H_n being linear transformations of $x(n)$, L_n and H_n are also monotonic on $(\tau_k, \tau_{k+1}]$. The extrema of H_n coincide with extrema of the original signal. The formula of defining these components of $x(n)$ on inter-extrema intervals allows the operation to be performed in a recursive manner, interval by interval, with the arrival of each new local extrema. Because the extracting operators $\mathcal{L}$ and $\mathcal{H}$ can be regarded as linear single-wave transformation, this method can be implemented in real-time with high computational efficiency.

Once the input signal is decomposed into a baseline L_n and a proper rotation component H_n, the process can be re-applied by setting the baseline signal L_n as an input. The iteration continues until a monotonic trend signal is obtained. Consequently, the iterations decompose the raw signal into a set of proper rotations. The overall procedure can be expressed as

$$\begin{aligned} x(n) &= \mathcal{H}x(n) + \mathcal{L}x(n) = \mathcal{H}x(n) + \left(\mathcal{H} + \mathcal{L}\right)\mathcal{L}x(n) \\ &= \left(\mathcal{H}\left(1 + \mathcal{L}\right) + \mathcal{L}^2\right)x(n) = \left(\mathcal{H}\sum_{k=0}^{p-1}\mathcal{L}^k + \mathcal{L}^p\right)x(n), \end{aligned} \quad (5)$$

where $x^k(n) = \mathcal{H}\mathcal{L}^k x(n)$ is a proper rotation extracted at $(k+1)$th iteration, $\mathcal{L}^p x(n)$ is the monotonic baseline signal representing the trend of $x(n)$, and p is the total number of iterations. The original ITD procedure requires a monotonic residual to ensure that all of the PRCs have been extracted. However, it is unnecessary for oscillation detection since the signal with only few extrema is not considered as a valid oscillation pattern. To tackle this issue, some recently proposed oscillation detection indexes (Guo et al., 2014; Zakharov et al., 2013) can be employed to terminate ITD at early stage.

2.2. K-means clustering

Given a set of samples $(z_1, z_2, \ldots, z_N)$ and each one is a real vector with same dimension. K-means clustering intents to partition the N observations into $K(<N)$ sets, $C = \{C_1, C_2, \ldots, C_K\}$, so as to minimize the following cost function (Beringer & Hüllermeier, 2006):

$$J_{MSE} = \sum_{i=1}^{K}\sum_{z \in C_j} \| z - c_i \|^2 \quad (6)$$

where c_i is the mean/center of the points in cluster C_j. Chapter 20 of MacKay (2003) elaborates the most commonly adopted iterative algorithm, Lloyd's algorithm, of determining the local optimum of Eq. (6).